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NEURO-FUZZY LOGIC CONTROL OF MPPT FOR INVERTER BASED WIND GENERATORS

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ABSTRACT

This research work investigates about the wind energy conversion system will receive the extensive attention among the various renewable energy systems by using an expert systems like Neuro-Fuzzy logics. The extraction of the maximum possible power available wind energy is an important area of research among the speed sensor less MPPT control of wind area. This paper discovers a power point tracking (MPPT) Technique for high performance wind turbine with induction machines based on expert systems (Artificial Neural Networks& Fuzzy logic system). In this paper, an ANN has been trained in off-line to learn about wind turbine characteristics of the torque with the wind speed and the speed of the machine which will be deployed in online for measuring the speed of the wind and torque and the fuzzy logic control is proposed here to evaluate the maximum power tracking point by the simulation and the results are shown. The reference speed of the machine is then calculated based on the control of the signal power feedback (PSF). Voltage oriented control of the machine is further integrated with an expert sensor less technique. The proposed method was simulated and conformed on the actual circuit in online.

***KEYWORDS:** Wind Generation, MPPT, Voltage Control, Computer Simulation, Wind Energy Conversion Systems, Incremental Conductance, Neuro-Fuzzy Systems*

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INTRODUCTION

Conservation of non-renewable energy motivates to explore the new avenues of resources for electricity generation which could be clean, safe and most valuable to serve the society for a long period. The option came with huge number of alternative sources which are the part of our natural environment and eco-friendly renewable energy sources. These sources can be better replacement of depleting non-renewable sources in order to meet the growing demand for power due to rapidly growing economy and increasing population. As per World Energy Outlook (WEO)-2010 the prospects for renewable energy based electricity generation hinge critically on government policies to encourage their development. Worldwide, the share of renewables in electricity supply increases from 19% in 2008 to 32% in 2035 in the New Policies Scenario; it reaches only 23% in the Current Policies Scenario, but 45% in the 450 Scenario. In all three scenarios, rising fossil-fuel prices and declining costs make renewables more competitive with conventional Hydropower has been the dominant renewable source of electricity for over a century. The recent strong growth in new technologies for wind power and solar photo voltaic (PV) has created expectations among policy makers and the industry alike that these technologies will make a major contribution to meet growing electricity needs in the near future. It has also been forecasted that the increase

in electricity generation from renewable sources between 2008 and 2035 will be primarily derived from wind and hydro power, which will contribute 36% and 31% of the additional demand respectively [1]. Wind power is projected to supply 8% of global electricity in 2035 up from just 1% in 2008. In the year 2010 the wind capacity has reached 196.630GW worldwide and it will reach 240GW by the end of 2011 as shown in Figure 1[2].

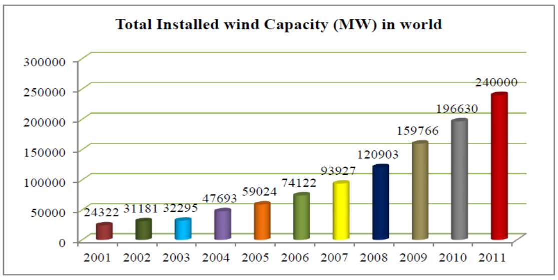

Figure 1: Statistical Data of Total Installed Wind Capacity in World

In high performance grid connected wind generators, the converter control is incorporated with any maximum power point tracking (MPPT) technique. According to the MPPT techniques, two main methods are presented in this paper: One is based on the torque control, and the other is based on speed control of the machine. The first method is based on the analytical expression of the optimal power torque as a function of the rotational speed of the machine, which is given as a reference to the power unit connected to the wind turbine. [3] The advantage is the simplicity of the technique, but the drawback is the torque control based drives, the base speed of the machine and the turbine speed should be, in any case, supervise online to prevent the system from having dangerous speed oscillations and go beyond the rated speed. Furthermore, the torque control means that no free variation result - the wind speed in a sudden torque variation in the machine. These rapid variations in torque do not lead to significant speed of the turbine due to the inertia of the system and thus create an inadequate mechanical stress on the shaft. By any contrast, in speed control of generators, at any sudden changes in wind speed is filtered by the control loop of the machine speed. In any case, torque controlled generators, the speed control is also essential for the generator to operate at high values of wind speed, where the values of power and torque exceed the rating of the machine. Finally, the torque control of the machine is based on the estimated torque, which can be affected by parameters mismatch and variations, with the consequent reduction of the maximum power. This is not the case in the speed control mode where the speed of the machine is generally measured with an encoder and the torque control loop is within the speed. Speed Control MPPTs are based on the incremental conductance method [21]–[25] or in appropriate relationships to calculate the reference speed of the optimum power unit on the basis of suitable modeling of wind turbine [4] - [8]. However, the latter often requires knowledge of the free wind speed, which must be measured or estimated correctly. One possible technique is the use of neural networks (NN), which was designed for an induction machine and uses two radial basis function (RBF), ANN for retrieving optimal rotor current and mechanical power. In this case, the free wind speed is estimated on the basis of the determination of the root of a polynomial by an iterative method (Newton-Raphson). However, only the results are given in numerical simulations This paper is also relates to an intelligent MPPT technique based on neural networks, only one ANN is used to calculate the reference speed, and control of high performance two converters back- to-back are adopted. Based on this and the knowledge of the power signal feedback (PSF), the reference power is generated either using a recorded maximum power curve or using the mechanical power equation of the wind turbine where wind speed or the rotor speed is used as the input. In PSF control, it is required to have the knowledge of the wind turbine's maximum power curve, and track this curve through its control mechanisms.

Additionally, the VOC system on the machine side has been integrated with an intelligent speed sensorless technique. The proposed wind-generation system is thus without speed sensors, which means that, it does not require the sensor for measuring the free wind speed, since the free wind speed is estimated by the ANN, and also, it does not require the machine-speed sensor (encoder), since the rotating speed is estimated by the TLS EXIN neuron with consequent significant system cost reduction and increased reliability. Finally, a comparison with a classic Incremental conductance MPPT has been made on a real wind-speed profile.

SYSTEM CONTROL TECHNIQUE

Incremental Conductance Method

Many algorithms have been developed for MPPT of a PV array [9] - [13]. Among the techniques of MPPT, the perturbation method and observation (P & O) is the most popular due to the simplicity of its control structure. However, in the present scenario it is rapidly changing with weather conditions, the P & O MPPT algorithm can be confused due to the fact that it is not able to distinguish variations in the output power caused by the tracker of disruption caused by varying irradiation [14] - [16]. Recently, improved P & O MPPT algorithms for changing environmental conditions have been proposed by Sera et al. [17]. The drawback of this method of P & O is the need to perform an additional measurement of energy in the middle of the MPPT sampling period to separate the effects of change of irradiation tracker disturbance. Herein, in order to generate the proper reference voltage under irradiation MPPT rapidly changing strong MPPT controller has been proposed. In this algorithm, the grid d-axis current component reflects off the power supply and the error signal of a voltage regulator external proportional-integral (PI) is designed to reflect the change in the power caused by irradiation variation. Therefore, with this information, the proposed algorithm can greatly reduce the power losses caused by tracking errors fast changing dynamic conditions of time. The superiority of the new proposed method is obtained based on the simulation results. The concept of incremental conductance method [21] - [25] is to determine the direction of variation of the terminal voltage of the PV modules by measuring and comparing the instantaneous conductance and incremental conductance photovoltaic modules. If the incremental conductance value equals the instantaneous conductance, which represents that there is the maximum power point. The basic theory is illustrated with Figure 2.

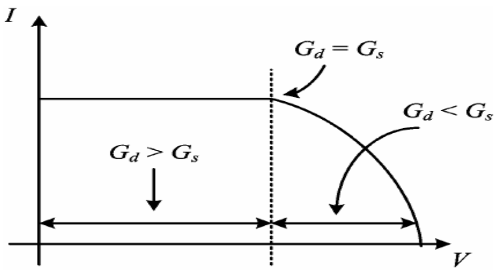

Figure 2: The Schematic Diagram of the Incremental Conductance Method

When the operating behavior of PV modules is within the constant current area, the output power is proportional to the terminal voltage. That means the output power increases linearly with the increasing terminal voltage of PV modules (slope of the power curve is positive, $dP/dV > 0$). When the operating point of PV modules passes through the maximum power point, its operating behavior is similar to constant voltage. Therefore, the output power decreases linearly with the increasing terminal voltage of PV modules (slope of the power curve is negative, $dP/dV < 0$). When the operating point of PV modules is exactly on the maximum power point, the slope of the power curve is zero ($dP/dV = 0$)

$$\frac{dP}{dV} = \frac{dVI}{dV} = I\frac{dV}{dV} + V\frac{dI}{dV} = I + V\frac{dI}{dV} \quad (1)$$

and can be further expressed as,

$$\frac{dI}{dV} = \frac{I}{V} \quad (2)$$

dI and *dV* represent the current error and voltage error before and after the increment respectively. The static conductance (G_s) and the dynamic conductance (G_d, incremental conductance) of PV modules are defined as follows,

$$G_s = \frac{1}{V} \quad (3)$$

$$G_d = \frac{dI}{dV} \quad (4)$$

The maximum power point (operating voltage is V_m) can be found

$$G_d|v = v_m = G_s|v = v_m \quad (5)$$

When the equation in (2) comes into existence, the maximum power point is tracked by MPPT system. However, the following situations will happen while the operating point is not on the maximum power point:

$$\frac{dI}{dV} > -\frac{I}{V}; (G_d > G_s, \frac{dP}{dV} > 0) \quad (6)$$

$$\frac{dI}{dV} < -\frac{I}{V}; (G_d < G_s, \frac{dP}{dV} < 0) \quad (7)$$

Equations (6) and (7) are used to determine the direction of voltage perturbation when the operating point moves toward to the maximum power point. In the process of tracking, the terminal voltage of PV modules will continuously perturb until the condition of (2) comes into existence. Figure 3 is the operating flow diagram of the incremental conductance algorithm.

The main difference between incremental conductance and P&O algorithms is the judgment on determining the direction of voltage perturbation. When static conductance *Gs* is equal to dynamic conductance *Gd*, the maximum power point is found [8]. From the flow diagram shown in Figure 3, it can be observed that the weather conditions don't change and the operating point is located on the maximum power point when *dV*= 0 and *dI*= 0. If *dV*= 0 but *dI*> 0, it represents that the sun irradiance increases and the voltage of the maximum power point rises. Meanwhile, the maximum power point tracker has to raise the operating voltage of PV modules in order to track the maximum power point. On the contrary, the sun irradiance decreases and the voltage of the maximum power point reduces if *dI*< 0. At this time the maximum power point tracker needs to reduce the operating voltage of PV modules.

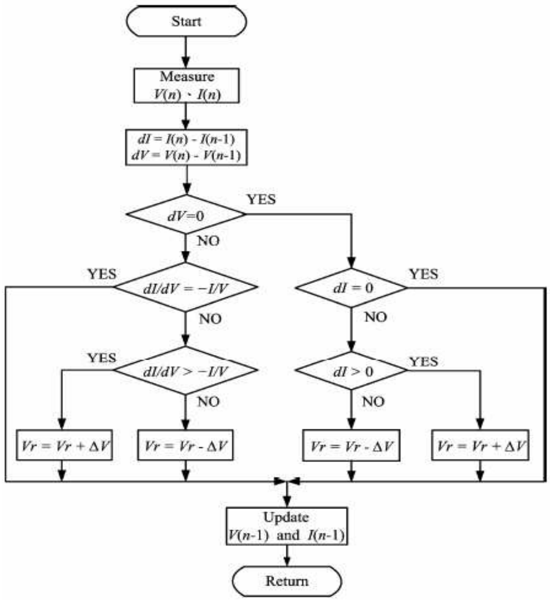

Figure 3: The Flow Diagram of the Incremental Conductance Method

Furthermore, when the voltage and current of PV modules change during a voltage perturbation and

$$\frac{dI}{dV} > -\frac{I}{V}\left(\frac{dP}{dV} > 0\right)$$

the operating voltage of PV modules is located on the left side of the maximum power point in the P-V diagram, and has to be raised in order to track the maximum power point.

$$\frac{dI}{dV} < -\frac{I}{V}\left(\frac{dP}{dV} < 0\right)$$

If the operating voltage of PV modules will be located on the right side of the maximum power point in the P-V diagram, and has to be reduced in order to track the maximum power point. The advantage of the incremental conductance method, which is superior to those of the other two MPPT algorithms, is that it can calculate and find the exact perturbation direction for the operating voltage of PV modules. In theory, when the maximum power point is found by the judgment conditions of the incremental conductance method, it can avoid the perturbation phenomenon near the

$$\left(\frac{dI}{dV} = -\frac{I}{V} and dI = 0\right)$$

maximum power point which is usually happened for the other two MPPT algorithms. The value of operating voltage is then fixed. However, it indicates that perturbation phenomenon is still happened near the maximum power point under stable weather conditions after doing some experiments. This is due to the reason that the probability of meeting condition

$\frac{dI}{dV} > -\frac{I}{V}$ is extremely small.

Voltage Control

A grid-side converter has been performed on the basis of a high-performance technique. VOC is based on the idea

of decoupling instantaneously the direct (*d*) and quadrature (*q*) components of the injected current, working in the grid voltage vector reference frame. In this synchronous reference frame, the voltage space-vector equations of the system are

$$u_g^u = u_{sg}^u \; + L\frac{di_{sg}^u}{dt} Ri_{sg}^u + j\omega L i_{sg}^u \tag{8}$$

The decomposition of such equations on the direct (*d*) and quadrature (*q*) axes gives

$$\begin{cases} u_{gd} = u_{sgd} + Ri_{sgd} + \dfrac{Ldi_{sgd}}{dt} - \omega L i_{sgq} \\ u_{gq} = u_{sgq} + Ri_{sgq} + \dfrac{Ldi_{sgq}}{dt} - \omega L i_{sgd} \end{cases} \tag{9}$$

Equation (9) shows that the direct component (quadrature) of the injected currents depends on the component of the voltages of the inverter. PI controllers are used to control the inverter current components in voltage oriented reference framework in the Simulink, as shown in Figure 4. However, as it is electrically powered counterpart, there is some coupling terms in both axis equations, which must be compensated with terms of feed-forward control. Since the objective here is to directly control the DC bus voltage, the control system has been slightly modified by adding loop of the dc- link voltage, external to the loop of the direct current components whose output current is direct reference. The reference quadrature current is always set to zero, so it is to maintain zero reactive power exchanged by the wind generation system with the grid.

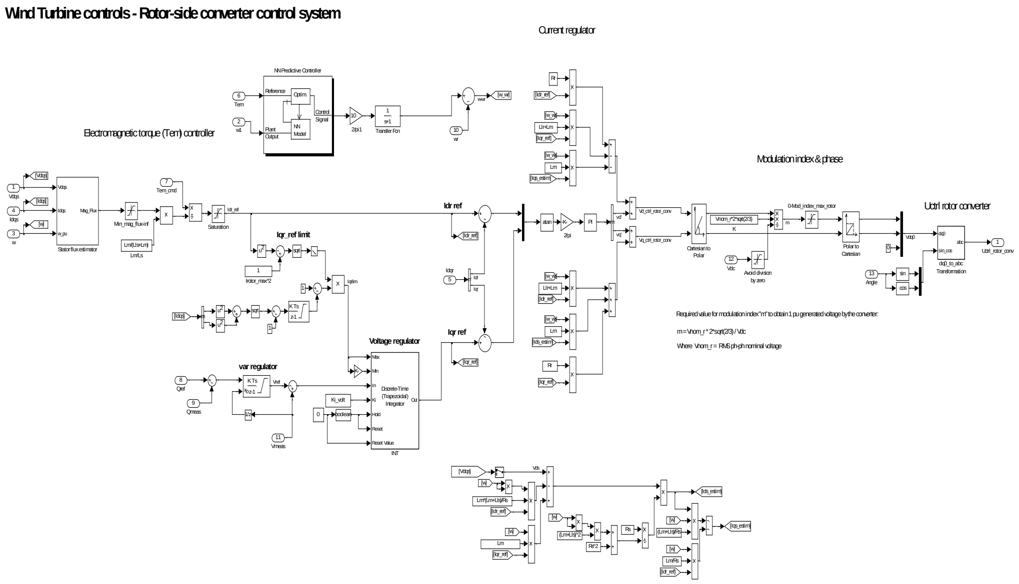

Figure 4: Wind Turbine Controls-Rotor Side Control System with VOC

WIND TURBINE SYSTEMS

Wind turbines produce electricity by using the power of the wind to drive an electrical generator. Wind passes over the blades, generating lift and exerting a turning force. The rotating blades turn a shaft inside the nacelle, which goes into a gearbox. The gearbox increases the rotational speed to that which is appropriate for the generator, which uses magnetic fields to convert the rotational energy into electrical energy. The power output goes to a transformer, which converts the electricity from the generator at around 700V to the appropriate voltage for the power collection system,

typically 33 kV. The power contained in the wind is given by the kinetic energy of the flowing air mass per unit time.

That is

$$P_{air} = \frac{1}{2}\rho A V^3_{\infty} \tag{a}$$

Where Pair is the power contained in wind (in watts), ρ is the air density (1.225 kg/m3 at 15°C and normal pressure), A is the swept area in (square meter), and V_{∞} is the wind velocity without rotor interference, i.e., ideally at infinite distance from the rotor (in meter per second).

$$C_p = \frac{P_{wind\ turbine}}{P_{air}}$$

$$= \frac{1}{2}\rho C_p A V^3_{\infty} \tag{b}$$

Power coefficient versus TSR Characteristics

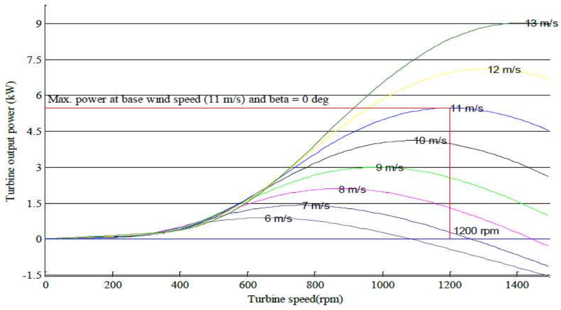

Figure 5: The Typical Power versus Speed Characteristics of a Wind Turbine

For a given wind turbine the power coefficient depends not only on TSR but also on the blade pitch angle. Figure 5 shows the typical variation of the power coefficient with respect to TSR (λ) with blade pitch control.

Where

$$\lambda = \frac{\omega R}{V\infty}$$

Where ω is rotational speed of rotor (in rpm), R is the radius of the swept area (in meter). The power coefficient (λ) and the power coefficient CP are the dimensionless and so can be used to describe the performance of any size of wind turbine rotor.

$$P_m = \frac{1}{2}\rho C p \pi R^2 V^3_{\infty}$$

For a given wind speed the power extracted from the wind is maximized if Cp is maximized. Always there is an optimum value of TSR for an optimum value of Cp (Cp-optimum). This means for varying wind speed the rotor speed should be adjusted proportionally to follow to the optimum value of TSR (λ optimum) for maximum mechanical power output from the turbine.

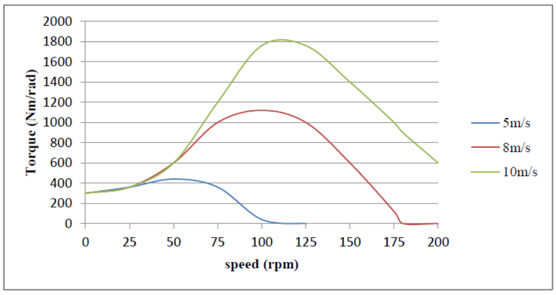

Figure 6: The Torque versus Speed Characteristics of Wind Turbine (Horizontal Axis Turbine)

$$T_m = \frac{P_m}{\omega} \tag{2.7}$$

The curve in Figure 6 shows that for any wind speed the torque reaches a maximum value at a specific rotational speed, and this maximum torque varies approximately as the square of rotational speed. In the case of electricity production the load torque depends on the electrical loading. The torque can be made to vary as the square of the rotational sped by choosing the load properly.

ANN MODEL BASED MPPT

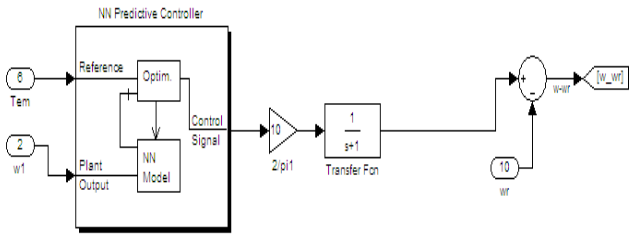

Figure 7: Simulink Diagram of the ANN-Based MPPT Algorithm

The basic idea of the proposed MPPT technique is to recover the optimal ω_{mrref} reference speed generator for any instantaneous value of the wind speed. Herein reference speed generator is calculated on the basis of the instantaneous values of the estimated torque and the measured speed, operating with the previous wind speed estimation. This allows one to have a technique based MPPT control of the speed of the machine in place of the torque control, with all the consequent advantages in terms of harmless operation and more stable the system. To calculate reference speed of the optimum machine, it is necessary to estimate the instantaneous values of the free wind speed.

FUZZY RULE BASED SYSTEM

The fuzzy logic controller (FLC) is proposed to find the MPPT [23]. The fuzzy logic control is somewhat easy to implement, as it requires no mathematical model to any system. Since it gives a study performance, and interest in the practical application of fuzzy logic is growing quickly. Fuzzy logic controllers are used to control important electrical and electronic devices as well as industrial processes. Many control methods based on fuzzy logic is possible to define control laws rather than equations because a fuzzy controller can be constructed based on empirical rules. A set of rules is constructed for classifying water quality as highly acceptable, just acceptable, not acceptable (rejected) in order to aggregate the set of attributes. Each rule has antecedent propositions connected together using AND operator, resulting in

some consequences. The assertions related to its antecedent part are obtained from the users, which are imprecise or fuzzy. Thus a fuzzy rule based system can be developed for the knowledge representation or reasoning process. Here the partial matching is allowed and the analyst can estimate the extent to which the assertion satisfies the antecedent part of the rule contrary to the rule- base system which examines as to whether the antecedent part is satisfied or not. Fuzzy Logic control incorporates a simple, rule-based IF X AND Y THEN Z approach to a solving control problem rather than attempting to model a system mathematically. The FL model is empirically-based, relying on an operator's experience rather than their technical understanding of the system. For example, rather than dealing with temperature control in terms such as "SP =500F", "T <1000F", or "210C <TEMP <220C", terms like "IF (process is too cool) AND (process is getting colder) THEN (add heat to the process)" or "IF (process is too hot) AND (process is heating rapidly) THEN (cool the process quickly)" are used. These terms are imprecise and yet very descriptive of what must actually happen. Consider what you do in the shower if the temperature is too cold: you will make the water comfortable very quickly with little trouble. FL is capable of mimicking this type of behavior but at very high rate.

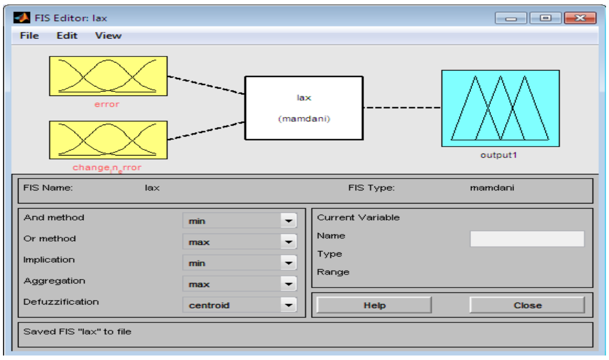

Figure 7a: Membership Function for MPPT

- **Fuzzification**

The numerical input variables CO and In CO are converted into linguistic variables based on the membership functions of Figure 2 with a=0,18 and b=0,36 for CO and a=0,14 and b=0,28 for Inc Co, respectively. Five linguistic variables are considered, they are PB (positive big), PS (positive small), ZE (zero), NS (negative small), NB (negative big).

- **Inferencing**

The logical products for each rule must be combined or inferred (max-min'd, max-dot'd, averaged, root-sum-squared, etc.) before being passed on to the defuzzification process for crisp output generation. Several inference methods exist

- **Defuzzification**

The RSS method was chosen to include all contributing rules since there are so few member functions associated with the inputs and outputs. For the ongoing example, an error of -1.0 and an error-dot of +2.5 selects regions of the "negative" and "zero" output membership functions. The respective output membership function strengths (range: 0-1) from the possible rules (R1-R9) are:

A "Fuzzy Centroid" Algorithm

The defuzzification of the data into a crisp output is accomplished by combining the results of the inference

process and then computing the "fuzzy centroid" of the area. The weighted strengths of each output member function are multiplied by their respective output membership function center points and summed. Finally, this area is divided by the sum of the weighted member function strengths and the result is taken as the crisp output. One feature to note is that since the zero center is at zero, any zero strength will automatically compute to zero. If the center of the zero function happened to be offset from zero (which is likely in a real system where heating and cooling effects are not perfectly equal), then this factor would have an influence. This type of the fuzzy is connected to the wind based system is as shown in figure 3.

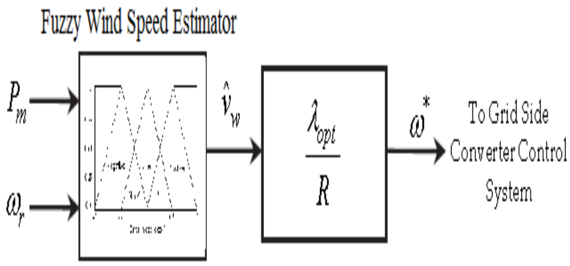

Figure7b: Fuzzy-Based MPPT Controller Module

RESULTS & ANALYSIS

In this application, an ANN with 1200 neurons has been adopted. In general, it could seem a high number but it should be noted that the ANN does not require the same computation effort as a classic multilayer perceptron trained by a back propagation algorithm with the same number of neurons. In this last case, as a matter of fact, adding any neuron to an existing NN structure implies the introduction of further nonlinear functions (sigmoid, Gaussian, etc.) depending on the position where the neuron is added (input, hidden, or output layer) with a consequent consistent increment of the computational requirement even in the production phase Modifying the number of neurons implies only storing a slightly different matrix. Afterward, online, only the recalling phase has to be implemented

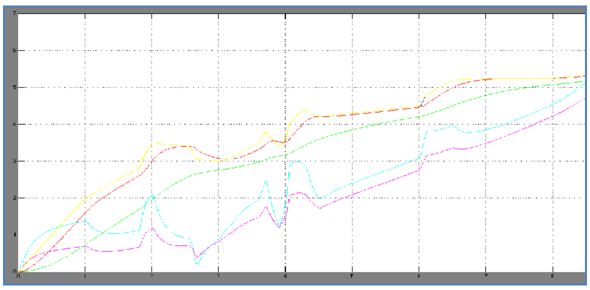

Figure 8: Wind-Speed Estimation with Different Numbers of Neurons

This implies that the computational demands required by ANN for this type of application is significantly less than that of a classic multilayer perceptron. Figure 8 shows the actual wind speed and estimated free wind speed during a simulated test composed of some parts in which the wind speed is constant and some others that are linearly variable. It shows the estimated wind speed with a different number of neurons, noting that the higher the number of neurons for the better the accuracy of the estimation, as expected. Note that there is no degradation of the accuracy of the estimation in transient wind speed, which is pretty good especially with 1200 neurons. Note that the oscillations in Figure 8 are due to the fact that different neurons belonging to the same group are activated depending on the variation of the input variable: If the resolution of the network is increased (higher number of neurons), then this ripple is reduced.

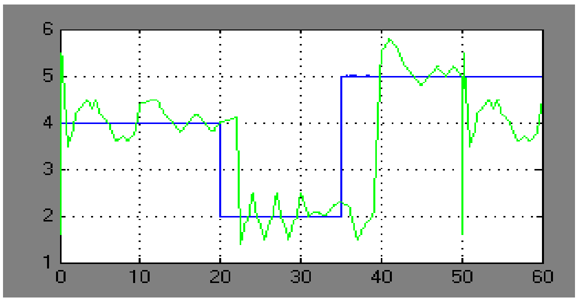

Figure 9: Real and Estimated Wind Speeds

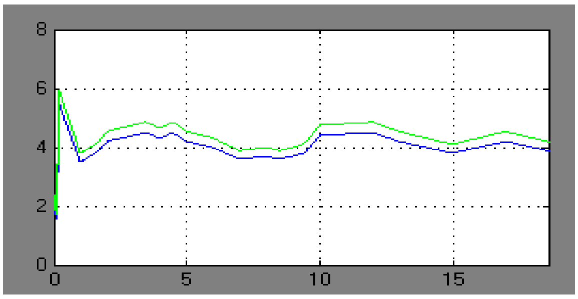

Figure 10: Estimated and Filtered Estimated Wind Speed

To show the best of the MPPT technique Artificial neural Network proposal based on coordinated with the sensorless control of the machine on the basis of the TLS EXIN neurons, in this test. The wind power generation system, works initially in steady state at a free wind speed of 2 m/s, has been given a set of free wind speeds: 4, 2 and 5 m/s. Some considerations must be made in this regard. The oscillations of the estimated wind speed and consequently the speed of the machine can significantly reduce.

As a result, the observer machine speed works in the worst conditions with the highest possible estimation errors in both the estimates of the rotor - flow and the speed, because of rapid speed machine transient. Estimation errors of machine speed and torque errors involve in wind speeds, which leads to a wrong calculation of the optimum machine reference speed. However, once the speed of the machine is approaching its reference, the torque and speed estimation errors decreases, and therefore, a new wind speed is estimated, which is very near to vary the actual again causing the reference speed of the machine. The lower transient errors ate estimated as shown in Figure 10. This is confirmed by the response of the system active power in figure 12a, 12b.

This means that the oscillations of the machine speed around its final value do not significantly affect the generated power, which, on average, gets to its final value after the first transient of the machine speed. Figure 11 shows the wind speed and the corresponding machine-speed variations when the rate of change of the wind speed is limited to 1000 m/s2, which is a very high value. It can be observed that a slight limitation of the wind-speed variation is sufficient to significantly reduce the oscillations of both the wind and machine estimated speeds. It should be noted that the machine speed estimated by the TLS EXIN full-order observer [18]-[19] properly tracks the measured one and its reference, thus highlighting the correct behavior of the TLS EXIN full-order observer also in generating mode.

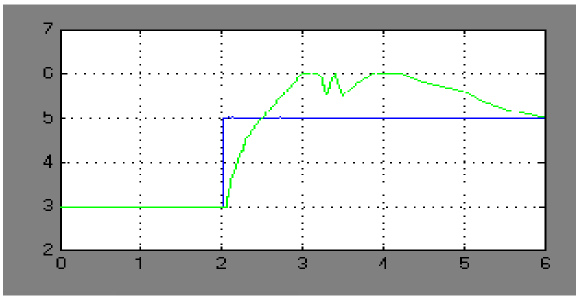

Figure 11: Wind and Machine Speeds with the Limitation of the Rate of Change of the Wind Speed to 1000 M/S^2

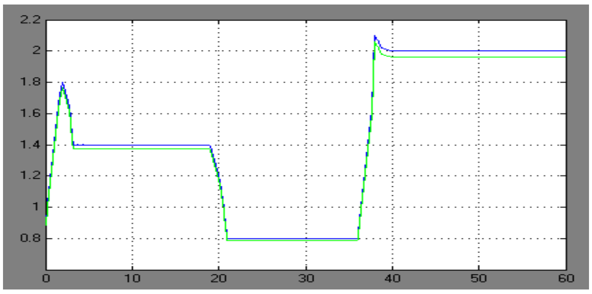

Figure 12a: Grid Side I_{sd}, I_{sq} Reference and Measured Currents

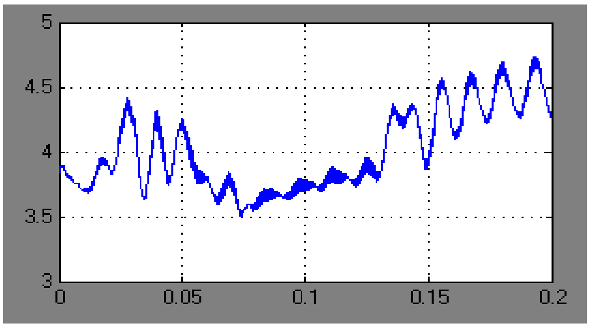

Figure 12b: Machine Side I_{sx}, I_{sy} Reference and Measured Currents

CONCLUSIONS

This paper presents an MPPT technique for high-performance wind turbine induction machines basedin integrating the estimated free - wind speed for Atrificial neural networks and machine speed estimate by the TLS EXIN full-order observer. The combined use of the estimation of the wind speed by Neuro-Fuzzy estimator and machine speedby the observer EXIN TLS causes the system to operate without any speed sensor neither a wind speed nor machine speed. Here, a network has been trained in online to learn the inverse turbine model using information provided by the direct model of the machine torque and speed of the machine. The reference speed of the machine is then calculated based on the relationship of power signal feed back (PSF) [20]. For directing a back to back configuration with two voltage source converters is considered, one side of the machine and the other on the network side. Each converter has been controlled with a vector control technique for high performance. Thus, no sensors are required wind speed machine. The simulation results show the correct behavior of the system, highlighting the performance of the proposed MPPT algorithm under sensorless observer. Finally, a comparison of proposed based Neuro-Fuzzy MPPT with the incremental conductance MPPT made in real profile wind speed has shown a better performance.

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